Multi-Scale Probabilistic Score Fusion for Enhancing Alzheimer's Disease Detection Using EEG

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Abstract: In this work, we propose a fusion approach to analyze EEG signals for the discrimination between patients with Subjective Cognitive Impairment (SCI) and patients suffering from Alzheimer's Disease (AD). In this framework, we analyze EEG signals at different epoch durations, following a multi-scale procedure, and in different frequency bands, using Phase-Lag Index (PLI) and Dynamic Time Warping (DTW) for functional connectivity measurement. Experiments show that our fusion approach leads to an improvement of classification results, reaching an AUC of 0.902 with PLI, and 0.894 with DTW; whereas we obtain an AUC of 0.845 with PLI and 0.801 with DTW when computing connectivity on the entire signal, as usually done in the literature. Furthermore, with the additional fusion of the scores obtained at different frequency bands, we reach the best performance with both PLI (AUC=0.95, Accuracy=91%) and DTW (AUC=0.98, Accuracy=95%). Finally, we investigate the generalization capability of our proposal on a test set. We found that our fusion scheme allows obtaining better classification results comparatively to when we consider the entire signal to compute functional connectivity.

1 INTRODUCTION

Dementia encompasses a group of disorders caused by the progressive dysfunction and death of brain cells. It affects memory, language, executive functions and other abilities, beyond what is considered a normal age-related change, with a significant impact on daily functioning.

The diagnosis of dementia relies on a series of clinical tests, including neurological tests and medical recordings. Neuroimaging techniques, such as Magnetic Resonance Imaging and Positron Emission Tomography Scanner are also used to assess the brain damage. These imaging tools are costly, non-portable, necessitate a hospital setting and the procedure can be complex and stressful for the patient. Moreover, they are unsuitable to follow-up the ongoing brain dynamics.

Electroencephalography (EEG) is a relatively low-cost and non-invasive neuroimaging technique that can be used either at clinical or home-based setting. EEG allows capturing brain dynamics with excellent time resolution in the millisecond range, which provides valuable insights into the brain's functioning. EEG brainwaves reflect the collective electrical impulses generated by the synchronized firing of neurons in the brain. These brainwaves manifest as rhythmic oscillations, typically categorized into several frequency bands; each associated with specific cognitive states and mental activities.

Alzheimer's disease (AD) is the most prevalent form of dementia, accounting for as much as 70% of all dementia cases (Castellani et al., 2010). It is estimated that 25 million people worldwide in 2010 were affected by AD. This figure will continue to grow, especially in Western countries as the world's population continues to age (Castellani et al., 2010), thus entailing high health care costs and a considerable human toll.

AD is characterized by progressive and irreversible brain damage. Disease progression typically spans over several years to decades. First, at the presymptomatic stage, the person has no symptom of AD and appears normal and unaffected, but AD-related changes are already taking place in the brain (Bossers et al., 2010). At the preclinical stage, the person may go through cognitive impairment and changes, but that are not detectable with standard tests yet.

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As there is no evidence of objective cognitive impairment, this condition is called “Subjective Cognitive Impairment" (SCI) (Dubois et al., 2009). Scientific community shows an increasing interest to this stage because of evidence of its association with an increased risk of future objective cognitive decline. Then, the patient may transition to Mild Cognitive Impairment (MCI) stage, on which memory and cognitive deficits start to be noticeable and measurable on cognitive tests. The patient then progresses to the Mild AD stage with notable cognitive deficits. These deficits continue to worsen in moderate and end-stage disease (Alz, 2024). There can be variations in the progression of AD and the precise symptoms can vary between patients.

Many studies have exploited resting-state EEG for AD diagnosis based on functional connectivity analysis, since AD is considered as a disconnection syndrome (Cassani et al., 2018). Various measures have been proposed to quantify functional connectivity, among them Phase-Lag Index (Abazid et al., 2021; Kasakawa et al., 2016; Stam et al., 2007), Phase Coherence (Dauwels et al., 2010b), Mean Square Coherence (Dauwels et al., 2010a), and Mutual Information (Abazid et al., 2021; Jeong et al., 2001). Functional connectivity values are computed pairwise between EEG signals. To analyze them, the common paradigm in the literature is to average the connectivity values per EEG electrode, or to group the electrodes into regions and to average the connectivity values per region (Dauwels et al., 2010b; Houmani et al., 2021). The resulting average values are then used as EEG-based features for AD detection, either in a statistical analysis or a model-based classification.

Given that the EEG signal is not stationary, it is usually segmented into epochs to calculate connectivity. The use of epochs for the extraction of EEG markers and their subsequent averaging across epochs has been shown to finely characterize connectivity; thereby enhancing the classification performance. However, a review of the literature reveals a considerable variability in the length of the EEG epochs employed in different studies (Cassani et al., 2018): from even less than one second (Knyazeva et al., 2010) to 30 seconds (Lee et al., 2010). The number of epochs used for EEG analysis also varies substantially in the literature (Cassani et al., 2018). Some studies analyze only one epoch (Abazid et al., 2021) but others can analyze as much as 200 per patient (Knyazeva et al., 2010). This is especially observed in research works exploiting deep learning algorithms. Generally, there is no explanation about the choice of the epoch duration and the number of epochs. Furthermore, the length of the entire EEG signal employed is seldom specified in the literature, which may give the impression that this parameter has a limited impact on the results. All theses facts collectively contribute to the variability and the inconsistency of the results presented across studies.

To our knowledge, no study in the literature has investigated the impact of signal duration and variation in the epoch duration on the classification performance. In this work, we aim at filling this gap. First, by studying the impact of varying EEG epoch duration on the classification of SCI and AD patients, based on functional connectivity. Second, by proposing a novel multi-scale fusion approach for EEG analysis combining classification score outputs derived from data analysis at different epoch durations. We investigate the effectiveness of our proposal using two alternative connectivity measures: Phase-Lag Index that is frequently used in the literature for AD diagnosis, and Dynamic Time Warping that allows two signals to be dynamically matched following their temporal variations (Karamzadeh et al., 2013). Furthermore, we propose to evaluate our fusion approach per frequency band and then by fusing them.

2 MATERIAL AND METHODS

2.1 Database Description

The cohort used to conduct this study is composed of resting-state EEG data of 32 SCI patients and 46 probable AD patients, acquired in a clinical setting at Charles-Foix Hospital (Ivry-sur-Seine, France). This retrospective study was approved by the institutional review board of the local Ethics Committee Paris 6 and the Ethics Committee of Sorbonne University (N°CER-2021-064).

The patients who complained of memory impairment were referred to the outpatient memory clinic of the hospital to undergo a battery of clinical tests for brain disorders. The diagnosis was set through a comprehensive clinical assessment, including neuroimaging, interviews, psychometric findings and neuro-psychological tests, in agreement with the standard diagnostic criteria: NINDS, DSM-IV, Jessen criteria for SCI (Jessen et al., 2014). It is noteworthy that EEG was not included in the battery of tests used to establish the diagnosis. Patients with epilepsy were excluded from the study. Table 1 reports demographic and clinical characteristics of patients included in the study.

EEG signals were recorded at rest with eyes closed during 20 minutes at a frequency sampling of 256 Hz, by taking care that the patients were not

Table 1: Clinical characteristics of the cohort. MMSE: Mini-Mental State Examination; SD: Standard Deviation.

	SCI (n=32)	AD (n=46)
Age (mean ± SD)	68.2 ± 10.4	82.0 ± 8.6
Female (%)	81.8%	67.4%
MMSE (mean ± SD)	28.3 ± 1.6	19.0 ± 5.6
Benzodiazepin use (%)	4 (18.2%)	10 (22.7%)
Antidepressant use (%)	5 (16.0%)	18 (39.1%)
Neuroleptic use (%)	0 (0.0%)	5 (11.0%)
Hypnotic use (%)	5 (15.6%)	8 (17.4%)

falling asleep. Thirteen electrodes were used, placed on the scalp according to the 10-20 international system: Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FC7, FC4, FT8, T3, C3, Cz, C4, T4, TP7, CP3, CPz, CP4, TP8, T5, P3, Pz, P4, T6, O1, Oz, and O2.

Then, EEG signals were visually inspected to discard the parts of the signals presenting artifacts (eye movements, eye blinks, muscular activity, instrumental noise etc.). Thereby, continuous signals of 20 seconds, free from artifacts, were then kept for the study. The obtained 20s-signals were then band-pass filtered with a third-order Butterworth filter in the frequency range (1-30 Hz), as well as in the four conventional frequency bands: delta (1-4 Hz), theta (4-8 Hz), alpha (4-8 Hz) and beta (12-30 Hz).

2.2 Methodology

In this work, we investigate the impact of varying EEG epoch duration on the discrimination of AD from SCI patients based on connectivity. To this end, we first segment the entire 20s EEG signal of each patient into epochs of different durations: 10s, 5s, and 2s. Therefore, for each patient, we obtain various EEG signals of different durations, *i.e.* the entire signal of length 20s, two epochs of 10s, four epochs of 5s and ten epochs of 2s.

Then, for each of these four time configurations, we compute functional connectivity (FC) between pairs of EEG signals, aggregated into eight regions. Figure 1 displays such regions: frontal/prefrontal (Fp1, Fp2, Fz), frontal left (F7, F3, FT7, FC3), frontal right (F4, F8, FC4, FT8), central (FCz, C3, CZ, C4), temporal left (T3, TP7, CP3, T5), temporal right (T4, CP4, TP8, T6), parietal (P3, Pz, P4), and occipital (O1, Oz, O2) regions.

To estimate the connectivity of one region, we average the FC values computed between the pairs of EEG signals associated to such region. For instance, for the frontal/prefrontal region, we average the connectivity values computed between Fp1 and Fp2, Fp1 and Fz, Fp2 and Fz. We also estimate the inter-regions connectivity by averaging the connectivity values computed between all pairs of EEG signals associated to such regions. For instance, for the connectivity between the prefrontal/frontal region and the occipital one, we take the mean of the connectivity values calculated between Fp1 and O1, Fp1 and Oz, Fp1 and O2, Fp2 and O1, Fp2 and Oz, Fp2 and O2, Fz and O1, Fz and Oz, Fz and O2.

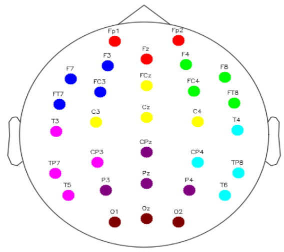


Figure 1: The 30 electrodes aggregated into 8 regions.

Finally, for each patient, each frequency band and each time configuration, we obtain a feature vector containing 36 average connectivity values, including 8 intra-region connectivity values and 28 inter-regions connectivity values.

To discriminate between SCI and AD patients, we use a Support Vector Machine (SVM) classifier (Campbell and Ying, 2011), considering only the most relevant features as inputs. These features are selected, from the total of 36 features, using the Forward Orthogonal Regression (OFR) method (Stoppiglia et al., 2003), to reduce the dimension of the input feature vector for the classifier. Classification performance is assessed on a development set, and then on a test set with the objective of evaluating the robustness of the proposed multi-scale fusion approach.

To validate our fusion approach, we exploit two FC measures relying on different mathematical concepts, namely Phase-Lag Index and Dynamic Time Warping distance.

2.3 Connectivity Measurement

2.3.1 Phase-Lag Index (PLI)

It is computed between pairs of EEG signals as follows (Stam et al., 2007):

$$PLI = |< sign(\Delta\Phi(t_k)) >| \quad (1)$$

where, |.| represents the absolute value, $\langle . \rangle$ indicates the mean (over index k), "*sign*" denotes the signum function that discards phase difference of 0 mod π and $\Delta\Phi(t_k)$ is the phase difference between two time series at time t_k.

PLI quantifies the asymmetry of the distribution of instantaneous phase differences between two signals, around zero mod π. If both signals are perfectly phase-locked at a value of $\Delta\Phi$, the resulting PLI value equals to 1. If both signals are either not coupled or are coupled with a phase difference centered at approximately 0 mod π, the PLI value will be close to 0. Intuitively, PLI allows quantifying the non-zero lags between two signals.

2.3.2 Dynamic Time Warping (DTW)

DTW distance (Senin, 2008) is an elastic matching metric that quantifies the dissimilarity between two time series showing a potential temporal drift. DTW reflects the amount of warping required to align two signals. It relies on finding the best warping path to match two signals by minimizing the cumulative distance between the assigned points in the two signals.

The computation of DTW distance between two EEG signals S_1 and S_2 of length N, consists in a recursive construction of the cost matrix, as follows:

$$\begin{aligned} DTW[i,j] = (S_1[i]-S_2[j])^2 + & \\ & min(DTW[i-1,j], \\ & DTW[i,j-1], \\ & DTW[i-1,j-1]) \end{aligned} \tag{2}$$

where, i and j are the time points for which we compute the DTW.

By design, the last computed value at coordinates (N, N) corresponds to the DTW value between the two signals. In order to optimize the aforementioned procedure for DTW calculation, it is sufficient to search the optimal path close to the main diagonal of the cost matrix, by applying a warping window. This corresponds to limiting the shifting that is allowed between matched observations of the two EEG signals. In this work, we used a Sakoe-Chiba band constraint (Sakoe and Chiba, 1978), with a warping window size fixed to six.

2.4 Performance Assessment Protocol

Classification was performed with a multivariate SVM, using only the most relevant features as mentioned earlier. The performance is assessed according to a consistent protocol: we generate 10 random samplings of the whole database, considering 22 SCI and 28 AD patients for the development set, 10 SCI and 18 AD for the test set.

For each of the 10 samplings, we follow the methodology outlined in Figure 2 for each frequency band and each time configuration. More precisely, on the development set, we first select the most relevant features among the computed 36 features, using the OFR method and random probe technique (Stoppiglia et al., 2003). The OFR allows ranking all the features (the original variables) in decreasing order of relevance. The random probe serves as a decision criterion to select the most pertinent features: we discard all features that are ranked after the probe, which is a realization of random variable considered as an additional feature. Therefore, the number of selected features differs for each time and frequency band configuration.

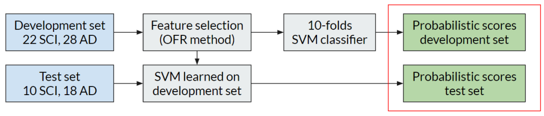


Figure 2: Experimental protocol for classification performance assessment.

Then, for each time configuration and frequency band, we perform a 10-folds SVM classifier with RBF kernel, and estimate the posterior probabilities of AD and SCI epochs using Platt's estimation method (Platt, 2000). Note that each patient has all his/her EEG epochs in the same fold, in order to overcome the issue of bias when evaluating the classification performance. Consequently, for each patient in the development set, we obtain one SVM probabilistic score associated to the 20s-signal, two SVM probabilistic scores associated to two 10s-epochs, four scores for the 5s-epochs, and ten scores of the 2s-epochs.

Classification performance is evaluated for each time configuration, separately, and then when fusing the SVM output scores obtained at different epoch durations.

On the test set, we assess the classification performance using the SVM model trained on the development set, considering the relevant features selected with the OFR method on the whole development set.

3 EXPERIMENTAL RESULTS

First, we present the results obtained on the development set in a progressive manner. More specifically, we present the classification results of SCI and AD epochs independently of the patient, for each time configuration (*i.e.* 20s-signal, 10s-epochs, 5s-epochs and 2s-epochs). Hence, we analyze the performance with four individual systems. Then, we analyze the classification results of SCI and AD patients, by averaging for each patient the SVM probabilistic

Table 2: AUC values on the development set using PLI and DTW to discriminate AD from SCI epochs, considering the four time configurations.

Frequency	Epoch	PLI	DTW
[1-30]Hz	20s	0.706	0.801
	10s	0.604	0.782
	5s	0.603	0.765
	2s	0.583	0.708
Delta	20s	0.544	0.751
	10s	0.608	0.738
	5s	0.579	0.746
	2s	0.543	0.720
Theta	20s	0.766	0.762
	10s	0.633	0.759
	5s	0.610	0.744
	2s	0.587	0.686
Alpha	20s	0.845	0.671
	10s	0.683	0.667
	5s	0.631	0.674
	2s	0.590	0.623
Beta	20s	0.642	0.755
	10s	0.652	0.777
	5s	0.633	0.789
	2s	0.563	0.770

Table 3: AUC values on the development set using PLI and DTW to discriminate AD from SCI patients, considering the four time configurations.

Frequency	Epoch	PLI	DTW
[1-30]Hz	20s	0.706	0.801
	10s	0.635	0.802
	5s	0.656	0.798
	2s	0.705	0.756
Delta	20s	0.544	0.751
	10s	0.644	0.754
	5s	0.651	0.781
	2s	0.603	0.788
Theta	20s	0.766	0.762
	10s	0.682	0.776
	5s	0.692	0.783
	2s	0.715	0.747
Alpha	20s	0.845	0.671
	10s	0.742	0.677
	5s	0.723	0.701
	2s	0.716	0.654
Beta	20s	0.642	0.755
	10s	0.689	0.786
	5s	0.701	0.810
	2s	0.618	0.805

output scores obtained on his/her EEG epochs, and that for each time configuration. After that, we evaluate the classification of SCI and AD patients when fusing with a simple average, per patient, the SVM scores associated to his/her epochs of different durations. Finally, on the test set, we assess the generalization capability of our fusion scheme, after training an SVM model on the entire development set.

3.1 Classification of SCI and AD Epochs

Table 2 summarizes the classification performance in terms of AUC (Area Under The Curve) when discriminating AD from SCI epochs with PLI and DTW. Results are given per frequency range, for each individual system (*i.e.* each time configuration). Each epoch was assigned to the class label of the corresponding patient.

Results indicate a good classification performance when estimating the PLI overall the 20s-signal for all frequency bands, except delta band. Also, we observe that the performance is degraded progressively when computing the PLI on shorter epochs, from 10s-epochs, 5s-epochs and then 2s-epochs.

When using DTW to quantify FC, we observe that there is not distinctive trend in performance between the 20s-signal and shorter epochs of 10s and 5s. However, the 2s-epoch configuration leads in general to the worst classification results.

3.2 Classification of SCI and AD Patients

Table 3 reports the AUC values obtained for each individual system using PLI and DTW to discrimate SCI from AD patients.

We note that the fusion of SVM output scores of epochs of a given time configuration leads to better classification performance, compared to the obtained results on separate epochs (see Table 2). However, no clear trend emerges on the relationship between performance and epoch duration in terms of AD and SCI patient classification. Based on the obtained result, we propose to go a step forward in our fusion scheme, by combining for each patient the SVM scores of his/her epochs with different durations.

3.3 Merging Probabilistic Output Scores of Different Epoch Durations

We average for each patient the SVM probabilistic scores obtained for his/her epochs with different durations. For example, to fuse the 20s and 10s, we average the output score associated to the 20s-signal and

Table 4: AUC values and correct classification rates (in %) of SCI and AD patients using PLI, when fusing SVM scores of different epoch durations (Acc: Accuracy, Sens: Sensitivity and Spec: Specificity).

Frequency	Time config.	AUC	Acc	Sens.	Spec.
[1-30]Hz	20s	0.706	69.4	88.9	44.5
	20s-10s-5	0.759	71.6	80.7	60.0
	20s-10s-5s-2s	0.789	75.6	77.9	72.7
	10s-5s-2s	0.760	72.4	78.2	65.0
Delta	20s	0.544	58.0	90.4	16.8
	20s-10s-5	0.693	64.4	79.9	45.0
	20s-10s-5s-2s	0.718	66.2	62.1	71.4
	10s-5s-2s	0.718	66.6	56.8	79.1
Theta	20s	0.766	73.4	73.6	73.2
	20s-10s-5	0.816	76.8	79.3	73.6
	20s-10s-5s-2s	0.844	80.2	86.8	71.8
	10s-5s-2s	0.799	74.4	81.1	65.9
Alpha	20s	0.845	77.8	82.9	71.4
	20s-10s-5	0.895	81.6	82.9	80.0
	20s-10s-5s-2s	0.902	83.6	89.6	75.9
	10s-5s-2s	0.835	78.4	83.2	72.3
Beta	20s	0.642	64.4	74.6	51.4
	20s-10s-5	0.765	71.8	72.9	70.5
	20s-10s-5s-2s	0.760	71.6	74.3	68.2
	10s-5s-2s	0.747	70.8	83.2	72.3

the two scores associated to the two epochs of 10s. Then, based on the average scores computed for all patients, we analyze the performance when discriminating AD from SCI patients.

Figures 3 and 4 display six ROC curves associated to the 20s-signal (baseline) and to five fusion configurations, considering respectively PLI and DTW as FC measures. We report in Tables 4 and 5 the results for the 20s configuration and only three fusion configurations, those leading to the best classification performance. Specificity is the percentage of SCI patients well classified; sensitivity indicates the percentage of AD patients well classified.

We observe that fusing the SVM scores of epochs with different durations allows to highly improving the classification of AD and SCI patients, compared to the baseline system (20s-signal), as well as to individual systems that have been fused (*i.e.* considering each time configuration separately). Indeed, in Section 3.2, the best AUC value is obtained with PLI in alpha considering the 20s-signal (AUC=0.845) and with DTW in beta considering the 5s-epoch (AUC=0.810). Nevertheless, when fusing the scores of epochs of different durations, we notice that better results are obtained for all fusion combinations, reaching an AUC value of 0.902 with PLI in alpha (see Table 4), and an AUC value of 0.894 with DTW in beta (see Table 5).

Additionally, we clearly observe that the fusion framework gives better results when combining the scores of the whole signal (20s-signal) with those of

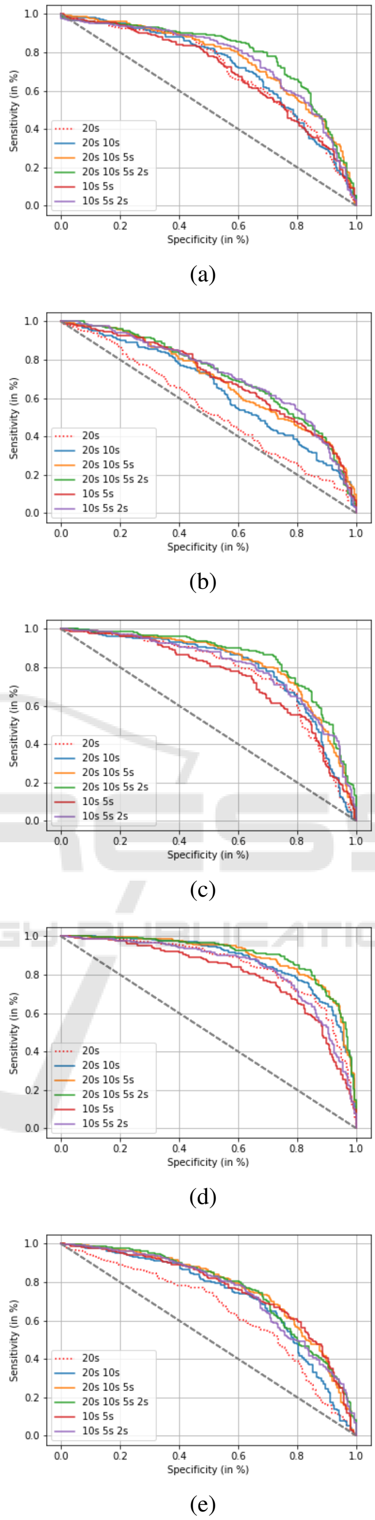


Figure 3: ROC curves for AD and SCI patient classification using PLI, when fusing SVM scores of different epoch durations in: (a) (1-30 Hz), (b) delta, (c) theta, (d) alpha and (e) beta.

Table 5: AUC values and correct classification rates (in %) of SCI and AD patients using DTW, when fusing SVM scores of different epoch durations (Acc: Accuracy, Sens: Sensitivity and Spec: Specificity).

Frequency	Time config.	AUC	Acc.	Sens.	Spec.
[1-30]Hz	20s	0.801	73.2	73.2	73.2
	20s-10s-5	0.884	81.2	83.9	77.7
	20s-10s-5s-2s	0.869	79.6	88.2	68.6
	10s-5s-2s	0.858	78.4	83.9	71.4
Delta	20s	0.751	70.0	73.2	65.9
	20s-10s-5	0.852	76.6	87.5	62.7
	20s-10s-5s-2s	0.882	79.6	88.2	68.6
	10s-5s-2s	0.873	80.0	83.6	75.5
Theta	20s	0.762	71.8	75.7	66.8
	20s-10s-5	0.868	79.6	83.9	74.1
	20s-10s-5s-2s	0.852	79.6	78.9	80.5
	10s-5s-2s	0.842	78.6	77.9	79.5
Alpha	20s	0.671	64.4	79.6	48.2
	20s-10s-5	0.766	70.8	80.7	58.2
	20s-10s-5s-2s	0.739	68.6	77.1	57.7
	10s-5s-2s	0.730	68.2	75.0	59.5
Beta	20s	0.755	70.4	66.8	75.0
	20s-10s-5	0.878	80.2	81.8	78.2
	20s-10s-5s-2s	0.894	80.4	78.2	83.2
	10s-5s-2s	0.887	79.8	78.9	80.9

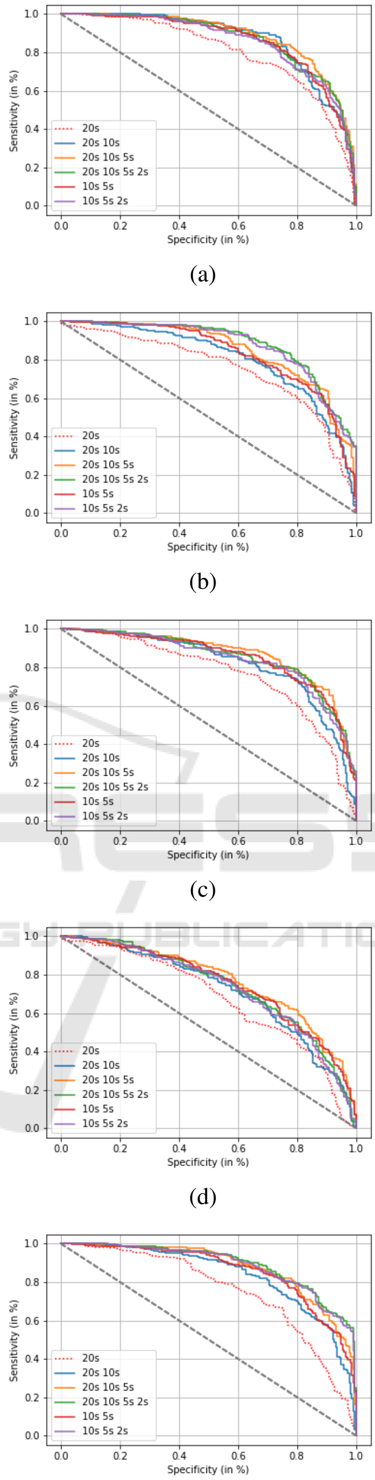
Table 6: AUC values and correct classification rates (in %) of SCI and AD patients using PLI and DTW, when fusing SVM scores of different epoch durations and different frequency bands (Acc: Accuracy, Sens: Sensitivity and Spec: Specificity).

Meas.	Time config.	AUC	Acc.	Sens.	Spec.
PLI	20s	0.910	83.8	92.1	73.2
	20s-10s-5	0.957	91.2	90.4	92.3
	20s-10s-5s-2s	0.956	91.0	92.1	89.5
	10s-5s-2s	0.929	87.0	88.2	85.5
DTW	20s	0.921	84.8	87.9	80.9
	20s-10s-5	0.986	94.4	95.0	93.6
	20s-10s-5s-2	0.987	95.0	94.3	95.9
	10s-5s-2s	0.984	94.0	92.1	96.4

shorter epochs in a progressive manner. The best results are obtained when fusing the scores of 20s-signal, 10s-epochs, 5s-epochs and 2s-epochs (20s-10s-5s-2s).

Table 6 and Figure 5 show the classification results when fusing for each patient the SVM scores of his/her epochs obtained at different time durations and in the four frequency ranges (delta, theta, alpha and beta). We observe that this double fusion scheme allows improving significantly the classification performance, reaching an accuracy value of 91.2% with PLI (AUC=0.95) and of 95% with DTW (AUC=0.98).

Finally, we remark that fusing the classification scores of the four frequency ranges is more powerful compared to when analyzing the signal on the whole spectrum (1-30 Hz). Indeed, when considering the



(a)

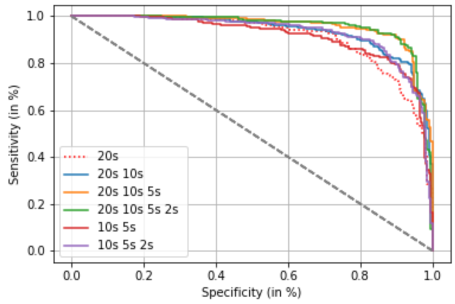
(b)

(c)

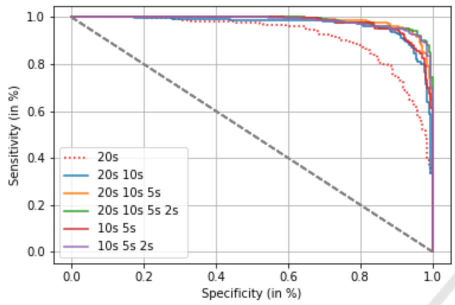
(d)

(e)

Figure 4: ROC curves for AD and SCI patient classification using DTW, when fusing SVM scores of different epoch durations in: (a) (1-30 Hz), (b) delta, (c) theta, (d) alpha and (e) beta.



(a)



(b)

Figure 5: ROC curves for AD and SCI patient classification using: (a) PLI and (b) DTW, when fusing the SVM scores of different epoch durations and different frequency bands.

whole spectrum, Tables 4 and 5 show that we reach an AUC value of 0.789 with PLI and of 0.884 with DTW, for the configuration (20s-10s-5s-2s). On such configuration, by processing EEG signals in each frequency band separately, and then fusing the resulting probabilistic scores, we obtain better results, reaching an AUC value of 0.957 with PLI and of 0.987 with DTW. This outcome also demonstrates the effectiveness of our fusion approach.

3.4 On the Generalization Capability of the Fusion Scheme on the Test Subset

In this section, we investigate the effectiveness of our fusing approach in terms of classification prediction on the test subset. We follow the experimental protocol explained in Section 2.4. Table 7 and Figure 6 show the results on the test set considering the whole 20s signal and the best configuration obtained on the development set, that fusing 20s, 10s, 5s and 2s.

The performance results on the test set are not good as those obtained on the development set. Nevertheless, we observe that fusing epoch durations allows enhancing the performance compared to when considering the 20s configuration, in terms of AUC and accuracy (see Table 7). This tendency is observed

Table 7: Classification performance on the test set using DTW, for the 20s-signal and the time configuration 20s-10s-5s-2s.

Frequency	Time config.	AUC	Acc.	Sens.	Spec.
[1-30]Hz	20s	0.758	74.3	82.8	59.0
	20s-10s-5s-2s	0.785	80.4	89.4	64.0
Delta	20s	0.690	66.8	97.8	11.0
	20s-10s-5s-2s	0.754	73.2	91.1	41.0
Theta	20s	0.679	70.0	72.8	64.0
	20s-10s-5s-2s	0.754	72.1	76.1	65.0
Alpha	20s	0.611	64.6	87.8	23
	20s-10s-5s-2s	0.670	70.4	80.6	52.0
Beta	20s	0.730	72.5	83.9	52.0
	20s-10s-5s-2s	0.761	75.4	89.4	50.0
Fusion	20s	0.776	74.6	92.2	43.0
	20s-10s-5s-2	0.803	80.4	93.3	57.0

for all the frequency bands. Moreover, the double fusion scheme, including both epoch durations and frequency ranges, allows increasing the performance even further (AUC=0.803).

Finally, note that we report only the generalization results obtained with DTW. In fact, the obtained results on the test set with PLI were very bad, reflecting that there is poor stability in the selected features with PLI from the development to the test sets, comparatively to DTW.

4 DISCUSSION

The purpose of this study is two folds: (i) investigating the impact of varying EEG epoch duration on the discrimination between two brain cognitive conditions (SCI and AD) based on functional connectivity, (ii) evaluating the potential application of a multiscale fusion approach for an improved classification results. We have proposed both temporal and frequency fusions, which consist in combining the classifier probabilistic scores obtained on epochs with different time durations and in different frequency bands. Such fusion was carried out through a simple averaging of the SVM scores which is the most parsimonious choice.

Experiments have been conducted following a consistent experimental protocol dividing the whole dataset into a development set and a test set. On the development set, results showed that when considering the whole 20s-signal (baseline system), the classification results of AD and SCI epochs are better than when analyzing EEG signals on shorter epochs of 10s, 5s and 2s. The worst results are obtained for the 2s-epoch duration.

By fusing, for each patient, the classifier output scores obtained on his/her epochs for each time

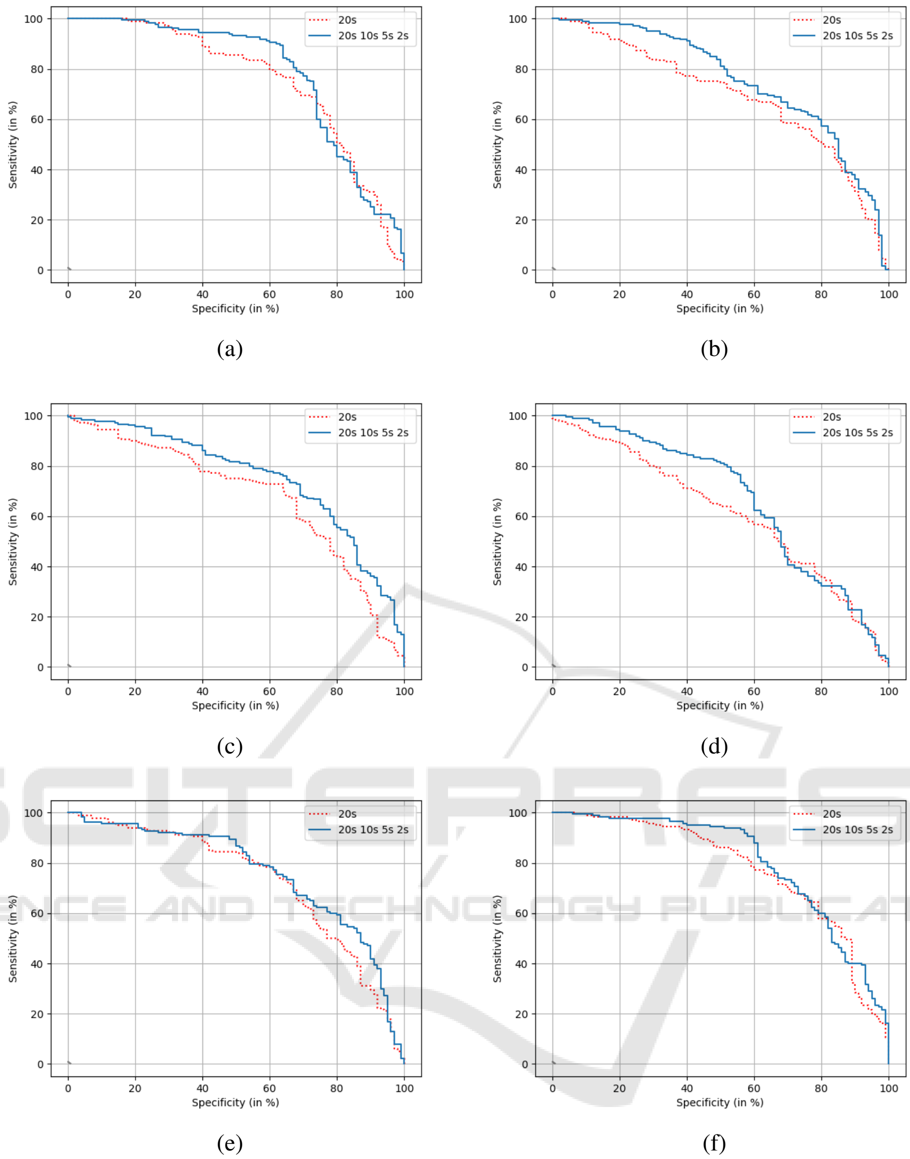


Figure 6: ROC curves for AD and SCI patient classification on the test set based on DTW, using the 20s-signal and the fusion configuration (20s-10s-5s-2s) in :(a) [1-30] Hz, (b) delta, (c) theta, (d) alpha, (e) beta, and (f) considering the fusion of all frequency bands.

configuration, classification performance of patients was found better than that obtained when classifying epochs. Nevertheless, no clear trend appeared on the relationship between epoch duration and classification performance. These results may highlight the potential complementarity in terms of information content, when segmenting EEG signals into epochs and fusing the classifier scores obtained per epoch.

Besides, our fusion approach showed an improvement of classification results when combining the scores of the whole signal (20s-signal) with those of shorter epochs in a progressive manner. The best results were obtained for the (20s-10s-5s-2s) configuration. Then, by fusing the classification scores obtained at different frequency bands, we further improve the discrimination between SCI and AD patients, reaching an accuracy of 91.2% with PLI (AUC=0.95) and 95% with DTW (AUC=0.98), with a very good balance between specificity and sensitivity. Results also highlighted that fusing classifier scores obtained in each frequency band is more efficient than when analyzing the signal on the whole spectrum. Notably, by analyzing each frequency band separately, we can retrieve more specific EEG features, which leads to a refined characterization of EEG signals and thus a better discrimination between populations.

When evaluating the results on the test set, we found that DTW is more effective than PLI in the context of this study. This can be explained by the fact that DTW is an elastic distance that allows capturing dynamic temporal-lags, which may fluctuate over time when matching two EEG signals. By contrast, PLI assumes the temporal delay stationary.

Although the classification results on the test set were degraded comparatively to the development set, our proposed multi-scale fusion approach outperforms the baseline system (20-s signal), reaching an AUC value of 0.785 for the 20s-10s-5s-2s configuration, and of 0.803 when additionally fusing the frequency bands.

All these results first highlight that varying EEG signal duration has an impact on the classification results. This can explain in part the difference of results in the state-of-the-art. Therefore, it is important to specify in scientific articles the duration of EEG signals and to clarify the epoching process, such as the number and length of epochs.

Furthermore, our findings demonstrate the effectiveness of analyzing EEG signals at different epoch durations and fusing the classification scores of the extracted epochs. This framework allows a refine characterization of the brain dynamics across time by computing the connectivity on short epochs, while taking into account all the available information in the whole EEG signal. Finally, combining the frequency bands is also very pertinent in terms of classification results, since each frequency band conveys valuable and complementary insights into brain function.

Our fusion scheme is based on classification scores. This study focuses on SVM probability output which entails two main limitations. First, probability estimation by Platt's assumes the relationship between the SVM scores and the probabilities to be sigmoidal, which might not be true in our case. However, our fusion scheme was evaluated in the same conditions as the individual systems. Second, we evaluate our approach with only one classifier. The results should be confirmed using other classifiers, leveraging alternative mathematical paradigms.

5 CONCLUSION

This work points out the potential use of both temporal and frequency fusion approach to improve the characterization of EEG signals, and thus the classification results of AD and SCI patients. In addition, this fusion approach allows obtaining good prediction performance in the context of generalization of results.

In the future, we will perform further analyses to study the extent of our fusion approach. First, we will analyze the features that were selected for the different durations of epochs to understand what are the crucial variables of the region connectivity matrix for the prediction. Second, we plan to investigate the effectiveness of our approach to discriminate between SCI, AD and MCI patients. Indeed, by adding the MCI group, the classification would be more challenging. Our hypothesis is that our multi-scale fusion approach can contribute to the fine characterization of these three cognitive conditions, thus enhancing the multi-class classification. Also, we will assess the generalization capability of other functional connectivity measures by conducting a comparative analysis in such context.

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